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Comparative Evaluation of Preprocessing Methods for MobileNetV1 and V2 in Waste Classification

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Abstract

Waste management remains a critical challenge for many countries, including Indonesia, which ranks as the world's second-largest contributor of waste. As tens of millions of tons are produced each year and the management system remains ineffective, environmental conditions and public health continue to deteriorate. To address this issue, it is imperative to develop more accurate and efficient solutions to enhance waste classification and management. This study investigates the influence of various image preprocessing techniques on the performance of MobileNetV1 and MobileNetV2 models in the classification of waste images. Preprocessing is crucial for enhancing data quality, particularly when dealing with real-world images that are affected by inconsistent lighting, texture, and clarity. Five preprocessing scenarios were evaluated: Baseline, CLAHE with Bilateral Filtering, CLAHE with Sharpening, Grayscale with CLAHE, and Gaussian Blur with Bilateral Filtering. Among these, the combination of CLAHE and Bilateral Filtering applied to MobileNetV1 achieved the best results, with 85% training accuracy, 96% validation accuracy, a training loss of 0.3178, and the lowest validation loss of 0.1630. Overall, MobileNetV1 benefited more significantly from preprocessing variations than MobileNetV2, particularly in terms of accuracy improvement and reduction in prediction error. These findings underscore the importance of effective preprocessing in enhancing model performance for waste image classification.

Keywords: waste; MobileNetV1; MobileNetV2; preprocessing; waste classification

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1. Introduction

Many countries, including Indonesia, are facing challenges in waste management [1]. Due to the high volume of waste generated from daily activities, particularly in urban areas, Indonesia has become the world's second-largest contributor of waste [2]. Waste refers to residues produced from various production processes, whether industrial or household, that are no longer useful after their intended use or processing has been completed [3]. Certain types of waste are difficult to decompose and can pollute the environment [4]. According to data from Sistem Informasi Pengelolaan Sampah Nasional (SIPSN), the waste generation in 367 regencies/cities across Indonesia is projected to reach 39,737,086.45 tons annually by 2023. Of this amount, only 13.61% has been successfully reduced, with the waste handling at 47.25% and a total of 60.85% of waste being managed. However, 39.15% of waste remains unmanaged [5].

Balanced waste management is crucial, as poor waste handling can lead to environmental degradation and pollution, negatively affecting human quality of life [6]. Waste is classified into two categories: inorganic waste, which consists of non-decomposable chemical materials, and organic waste, which is composed of natural, biodegradable materials [7]. Inorganic waste, which is particularly difficult to break down in soil, often causes long-term pollution [8]. Therefore, an efficient waste management system is essential to minimize the environmental impact of waste.

Modern technology can be leveraged to enhance the accuracy and efficiency of waste classification processes [9]. For example, waste classification using Convolutional Neural Network (CNN) algorithms has achieved an accuracy of 89% and a validation accuracy of 61% [10]. Similarly, the EfficientNetB0 architecture has demonstrated 88.53% accuracy with a loss of 41.41% [11], while the VGG16 architecture has reported 82.89% accuracy and 84.62% validation accuracy [12].

Other studies on classification tasks have also explored the MobileNet architecture, including MobileNetV1 and MobileNetV2, which are well-known for their efficiency and adaptability in resource-constrained environments [13]. Previous research has demonstrated that MobileNetV1 can achieve high accuracy in various classification tasks, such as brain tumor classification, handwritten character recognition, and other classification challenges, with efficient performance on mobile devices [14], [15], [16]. For instance, MobileNetV1 was successfully applied to detect brain tumors from MRI images, achieving an accuracy of 97% [14]. It also achieved 90% accuracy in identifying different types of freshwater fish [15] and 96.46% accuracy in recognizing 231 classes of Bangla handwritten characters [16].

A study analyzing eight deep learning architectures [17] revealed that the MobileNet architecture outperformed other models in terms of performance. Another study demonstrated that while MobileNet models can achieve high accuracy in classifying various waste types, significant challenges arise when images contain objects with similar and complex shapes, which can increase the likelihood of prediction errors [18]. Furthermore, another study emphasized the importance of applying filtering-based preprocessing techniques to address these challenges [19]. For instance, a study on lung disease classification using MobileNet highlighted that proper preprocessing methods could significantly enhance model performance in classification tasks [20]. These findings indicate that effective data processing strategies are a crucial factor in improving image classification accuracy.

MobileNetV2 has been applied to various image classification tasks, including plant disease detection, melanoma identification, lung disease diagnosis, and waste classification [21], [22], [23], [24]. For tomato leaf disease classification, the model achieved an accuracy exceeding 90% [21]. In melanoma classification, it reached over 85% accuracy, despite challenges related to class imbalance [22]. Similarly, in lung disease prediction, the model achieved an accuracy of over 90%, but low sensitivity due to imbalanced class distribution remained a challenge [23]. In waste classification involving four categories, achieved an accuracy of 82.92% [24].

The performance of a model in object identification is not solely determined by the type of CNN architecture employed, but is also influenced by the preprocessing stages applied to the dataset prior to training [19]. Moreover, preprocessing techniques can significantly impact the model's accuracy level [25]. In this study, we work with a waste image dataset that presents several challenges, including variations in lighting, differences in texture, and visual detail complexity. These variations have the potential to degrade model performance if not properly addressed through adequate preprocessing procedures.

Therefore this study aims to conduct a comparative evaluation of various preprocessing methods to determine the most effective approach for enhancing the performance of MobileNetV1 and MobileNetV2 in waste classification. Comparing preprocessing techniques across both models is crucial for understanding how each architecture responds to different data treatments. Consequently, this research not only examines the effectiveness of preprocessing but also addresses a research gap concerning the relationship between preprocessing strategies and model architectures in the context of waste classification.

The dataset utilized in this study consist of 630 images sourced from Waste Bank Bougenville in Magelang. The research findings are anticipated to aid in identifying the optimal combination of preprocessing methods and model architecture for waste classification.

2. Methods

The research was conducted through several stages, as illustrated in Figure 1, which presents the research workflow. Two models were utilized in this study: MobileNetV1 and MobileNetV2. In each scenario, the models were trained using various parameters. Two models were subsequently tested, and the result from different scenarios were compared to identify the best scenario based on the highest accuracy achieved.

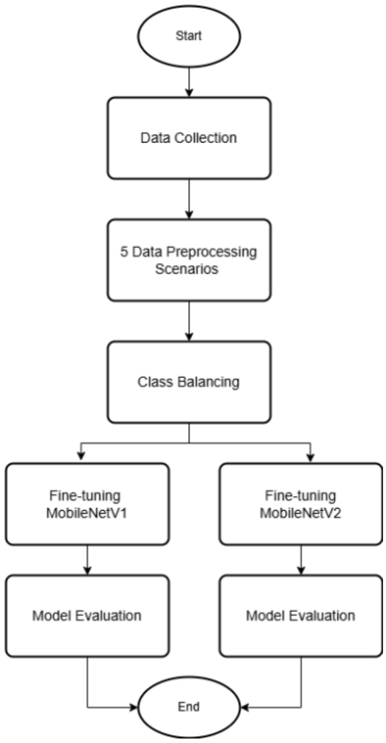


Figure 1. Research Workflow

2.1 Data Collection

The data were collected directly at the Waste Bank Bougenville in Magelang using a high-resolution web camera. The dataset obtained consisted of 630 images, comprising 370 images of inorganic waste and 260 images of organic waste. All images were resized to 224x224 pixels to fit the MobileNet architecture.

The disparity in the number of inorganic and organic waste images could affect the model training process. Therefore, steps were taken to balance the dataset distribution to minimize bias in the models. Figure 2 and 3 illustrate the differences in the characteristics of inorganic and organic waste. Inorganic waste tends to exhibit distinctive geometric shapes and reflective surfaces. In contrast, organic waste is characterized by irregular textures and natural patterns.

Figure 2. Inorganic Waste

Figure 3. Organic Waste

2.2 Data Preprocessing

Data preprocessing aims to enhance the quality of images, enabling the model to learn from cleaner and more informative data. Table 1 outlines the preprocessing scenarios applied in this study.

Table 1. Preprocessing Scenarios

Alias	Scenario
S1	Baseline
S2	CLAHE + Bilateral Filtering
S3	CLAHE + Sharpening
S4	Grayscale + CLAHE
S5	Gaussian Blur + Bilateral Filtering

Five preprocessing scenarios were designed to evaluate their impact on the model's performance (Table 1). The first scenario, referred to as the Baseline (S1), consist of the original images without the any additional processing and serves as the fundamental benchmark for comparison. In the second scenario, CLAHE + Bilateral Filtering (S2), Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied to improve image contrast [26], followed by bilateral filtering to smooth the image while preserving edge information [27]. This method aims to enhance contrast without compromising fine details.

The third scenario, CLAHE + Sharpening (S3), combines CLAHE with a sharpening technique to enhance the visual sharpness of image elements [28]. Thereby improving edge clarity. The fourth scenario, Grayscale + CLAHE (S4), begins by converting images to grayscale, capturing intensity variations from black to white [29], followed by the application of CLAHE to further enhance detail. Finally, the fifth scenario, Gaussian Blur + Bilateral Filtering (S5), applies gaussian blur to smooth images by reducing noise and reflections [30], followed by bilateral filtering. This combination is intended to mitigate high-frequency noise while preserving important edge details.

2.3 Class Balancing

The next step involves class balancing using the class weighting method as shown in Equation 1 to address the imbalance in the number of data points across classes [31]. This method was chosen because it effectively balances the weights among classes in an uneven dataset, allowing the model to pay greater attention to classes with fewer samples.

$$Weight = \frac{n\_samples}{(n\_classes * np.bincount(y))} \tag{1}$$

Where *n_samples* represent the total number of samples in the dataset, *n_classes* is the number of distinct classes, and *np.bincount(y)* counts the number of samples for each class. Using this approach, the weights for each class can be calculated as Equations 2 and 3.

$$Weight\ (Inorganic) = \frac{630}{2\,x\,370} = \frac{630}{740} \approx 0.851 \tag{2}$$

$$Weight\ (Organic) = \frac{630}{2\,x\,260} = \frac{630}{520} \approx 1.212 \tag{3}$$

Based on the results, it is evident that the organic class, which has a smaller number of samples compared to the inorganic class, receives a higher weight of approximately 1.212, compared to the inorganic class, which has a weight of around 0.851.

2.4 Fine-tuning MobileNetV1 and MobileNetV2

MobileNetV1 and MobileNetV2 are Convolutional Neural Network (CNN) architectures selected in this study for their ability to process data quickly, accurately, and efficiently, even on devices with computational limitations [32]. At this stage, several parameters were optimized to enhance the performance of the proposed model. Fine-tuning was applied by unlocking several of the model's final layers to improve accuracy. This selection of the fine-tuning parameters was conducted using a trial-and-error approach, testing various training parameters to identify the optimal configuration. The training process was performed using TensorFlow, supported by hardware equipped with a GPU and 16GB of RAM, sufficient to handle the model training process.

Table 2. Proposed Hyperparameters

Parameter	Value
Learning Rate	1e-5
Batch Size	32
Epoch	10
Optimizer	Adam
Data Train	70 %
Data Validation	15%
Data Test	15%

Table 2 presents the hyperparameters used in this experiment. These hyperparameters were applied across all preprocessing scenarios and both architectures tested. For a more detailed explanation of the proposed model architectures, readers are referred to Tables 3 and 4, which illustrate the layer structures of MobileNetV1 and MobileNetV2 after fine-tuning.

Table 3. Proposed Layers in MobileNetV1

Layer (Type)	Output Shape	Param #
input_layer	(None, 224, 224, 3)	0
global_average_pooling2d	(None, 1024)	0
dense	(None, 512)	524,800
batch_normalization	(None, 512)	2,048
dropout	(None, 512)	0
dense_1	(None, 2)	1,026

Table 4. Proposed Layers in MobileNetV2

Layer (Type)	Output Shape	Param #
input_layer	(None, 224, 224, 3)	0
global_average_pooling2d	(None, 1280)	0
dense	(None, 512)	655,872
batch_normalization	(None, 512)	2,048
dropout	(None, 512)	0
dense_1	(None, 2)	1,026

Tables 3 and 4 detail the modifications applied to both models, including the addition of several layers in MobileNetV1 and MobileNetV2. These modifications encompass the implementation of a Global Average Pooling layer, a Dense layer with 512 units utilizing the ReLU activation function, and the application of Batch Normalization. To mitigate the risk of overfitting, a Dropout layer is incorporated, followed by an output Dense layer with a softmax activation function that generates probabilities for two classes.

3. Results and Discussions

The result of the five preprocessing scenarios are visualized to illustrate the effect of each method on the appearance of waste images. Figures 4, 5, 6, 7, and 8 display the waste images after preprocessing.

Figure 4. S1 (Baseline)

In Figure 4, the output of S1 represents the original image without any additional preprocessing methods. The color and details remain identical to the raw data. This first scenario serves as the primary baseline for evaluating the effectiveness of other preprocessing methods in improving model performance.

Figure 5. S2 (CLAHE + Bilateral Filtering)

The second scenario employs CLAHE followed by Bilateral Filtering methods. As shown in Figure 5, the results of these methods yield smoother image textures while preserving clear edge details.

Figure 6. S3 (CLAHE + Sharpening)

The third scenario applies CLAHE and Sharpening methods. In Figure 6, the preprocessing results reveal images with sharper edges and enhanced contrast.

Figure 7. S4 (Grayscale + CLAHE)

The fourth scenario, Grayscale and CLAHE methods are used. The results, presented in Figure 7, show images with more focused details in grayscale, effectively minimizing distractions from irrelevant color information.

Figure 8. S5 (Gaussian Blur + Bilateral Filtering)

The fifth scenario utilizes Gaussian Blur and Bilateral Filtering methods. The results, illustrated in Figure 8, exhibit images with smoother textures while maintaining critical elements such as the edges of waste objects.

3.1 Model Performance Comparison

In this section, a performance comparison is conducted between MobileNetV1 and MobileNetV2 using five preprocessing scenarios as previously described. The performance comparison results of these two models are presented in Table 5, including training accuracy, validation accuracy, and loss value for each scenario of both models.

Based on the results shown in Table 5, scenarios S1-V2 and S2-V2 achieved the highest training accuracy at 86%, while S2-V1 recorded the highest validation accuracy at 96%. On other hand, for training loss and validation loss, S2-V1 demonstrated the lowest values, with 0.3178 and 0.1630, respectively. Although S1-V2 and S2-V2 achieved slightly higher training accuracy (86%) compared to S1-V1, S2-V1, and S3-V1, which each recorded 85%, the S2-V1 scenario stood out with higher validation accuracy and lower validation loss than other scenarios. This indicates that the preprocessing method applied in S2-V1 significantly impacts improving validation performance. S2-V1 successfully achieved the highest validation accuracy of 96% and the lowest loss value among all tested scenarios and models, demonstrating its capability to generalize unseen data effectively

Table 5. Performance of MobileNetV1 and MobileNetV2

Alias	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss	Alias	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
S1-V1	85%	95%	0.3296	0.1665	S1-V2	86%	93%	0.3463	0.2358
S2-V1	85%	96%	0.3178	0.1630	S2-V2	86%	90%	0.3690	0.2421
S3-V1	85%	93%	0.3540	0.2084	S3-V2	84%	88%	0.3827	0.2984
S4-V1	83%	90%	0.3646	0.2180	S4-V2	83%	86%	0.3894	0.3245
S5-V1	84%	87%	0.4362	0.2753	S5-V2	83%	89%	0.4217	0.2748

Interestingly, the S1-V2 scenario in MobileNetV2, which does not employ additional preprocessing methods (baseline), demonstrates a more optimal performance compared to other scenarios in MobileNetV2. The S1-V2 scenario successfully maintains good training accuracy (86%) and achieves relatively lower validation loss values despite the absence of additional preprocessing techniques. Conversely, scenarios S2 through S5, which incorporate various additional preprocessing methods. Do not show significant performance improvements in the MobileNetV2 model. Certain scenarios, such as S4-V2 and S5-V1, even demonstrate a decrease in accuracy and an increase in loss. Notably, S4-V2 records the lowest validation accuracy (86%), while S5-V1 shows a relatively high training loss value (0.4362).

In MobilNetV1, the S2-V1 scenario provides the best performance, whereas in MobileNetV2, the S1-V2 scenario (without additional preprocessing) yields more optimal results. This suggests that, for certain models, implementing preprocessing may not always deliver significant advantages and could even risk reducing performance. Moreover, although MobileNetV2 generally exhibits slightly better training accuracy, MobileNetV1 with the S2-V1 scenario still outperforms in terms of validation accuracy and validation loss. This highlights the importance of selecting appropriate preprocessing methods and aligning them with the model's characteristics to achieve optimal performance.

Table 6 illustrates a comparison of preprocessing times across various training scenarios using MobileNetV1 and MobileNetV2.

Based on the data presented in Table 6, there is a significant difference in training time between MobileNetV1 and MobileNetV2. MobileNetV1 consistently demonstrates faster training times compared to MobileNetV2 across all scenarios. The shortest training time for MobileNetV1 is recorded in scenario S1 at 86.51 seconds, while its longest training time occurs in scenario S2 at 89.66 seconds. Meanwhile, MobileNetV2 achieves its shortest training time in scenario S2 at 98.20 seconds and its longest training time in scenario S1 at 99.87 seconds. This indicates that MobileNetV1 is more efficient in processing data than MobileNetV2, particularly during the training phase. This efficiency can be attributed to the simpler architecture of MobileNetV1, which reduces computational Complexity.

Table 6. Time Preprocessing Methods

Scenario	Timer
S1-V1	86.51s
S2-V1	89.66s
S3-V1	88.16s
S4-V1	88.31s
S5-V1	87.05s
S1-V2	99.87s
S2-V2	98.20s
S3-V2	99.81s
S4-V2	98.38s
S5-V2	98.77s

3.2 Model Evaluation

Model evaluation was conducted to measure the performance of MobileNetV1 and MobileNetV2 in classifying data into two categories: organic waste and inorganic waste. The evaluation results are presented using a classification report and a confusion matrix. These metrics were chosen to provide a comprehensive understanding of the model's performance from various perspectives, including overall precision, recall, F1-score. Table 7 summarizes the classification report results, while Figure 9 visualizes the confusion matrix, illustrating the distribution of correct and incorrect predictions for each class. This analysis is used to identify patterns of classification errors.

Table 7. Classification Report

Alias	Precision	Recall	F1-score	Alias	Precision	Recall	F1-score
S1-V1	92%	91%	91%	S1-V2	92%	91%	91%
S2-V1	93%	92%	92%	S2-V2	89%	86%	87%
S3-V1	93%	92%	92%	S3-V2	84%	78%	78%
S4-V1	92%	91%	91%	S4-V2	90%	86%	87%
S5-V1	89%	86%	87%	S5-V2	89%	88%	89%

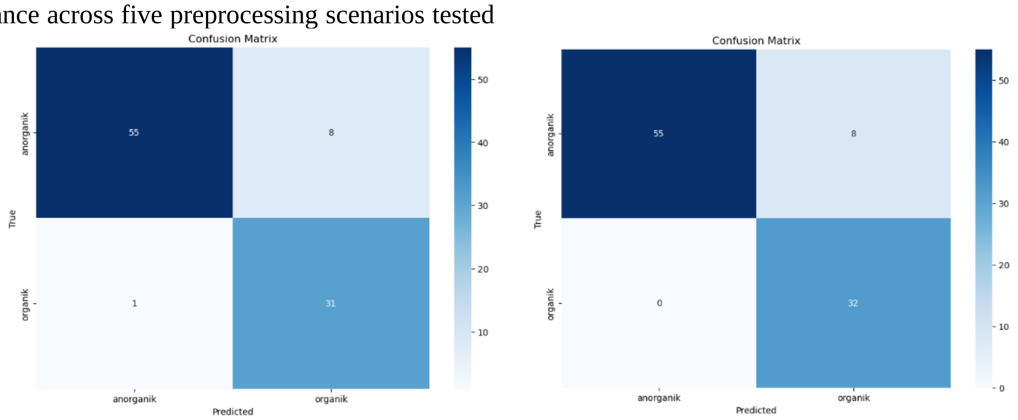
Based on Table 7, the evaluation results indicate that MobileNetV1 outperforms MobileNetV2 across various scenarios. In scenarios S2-V1 and S3-V1, MobileNetV1 achieved the highest precision, recall, and F1-score values of 93%, 92%, and 92%, respectively. Conversely, MobileNetV2 demonstrated its best performance in scenario S1-V2, with precision, recall, and F1-score values of 92%, 91%, and 91%. However, MobileNetV2 experienced a significant performance decline in scenario S2-V2, with precision, recall, and F1-score dropping to 89%, 86%, and 87%. A further decrease was observed in scenario S3-V2, where the precision, recall, and F1-score fell to 84%, 78%, and 78%. This is in stark contrast to MobileNetV1, which exhibited its best performance in scenarios S2-V1 and S3-V1.

In scenario S4, MobileNetV1 again outperformed MobileNetV2, achieving precision, recall, and F1-score values of 92%, 91%,, and 91%, compared to MobileNetV2's 90%, 86%, and 87%. Nevertheless, in scenario S5, MobileNetV2 showed improvement, with recall and F1-score values of 88% and 89%, slightly surpassing MobileNetV1's S5-V1 performance, which recorded recall and F1-score values of 86% and 87%. The precision for both models in scenario S5 remained the same at 89%. Overall, MobileNetV1 demonstrated more consistent and superior performance across various scenarios compared to MobileNetV2, indicating that MobileNetV1 is more reliable in handling the data variations used in this study.

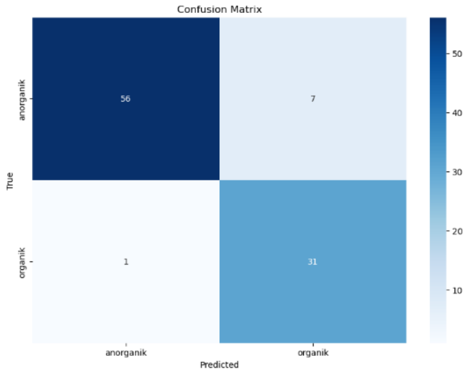
In Figure 9, the confusion matrix illustrates the performance across five preprocessing scenarios tested using MobileNetV1 and MobileNetV2. The results reveal that the S2-V1 configuration achieved the lowest prediction error rate, with only 8 errors (8 misclassifications occurred where inorganic waste was predicted as organic waste, and no errors were found in predicting organic waste as inorganic waste). This indicates that the combination of CLAHE and Bilateral Filtering delivers the most stable and accurate performance compared to other scenarios.

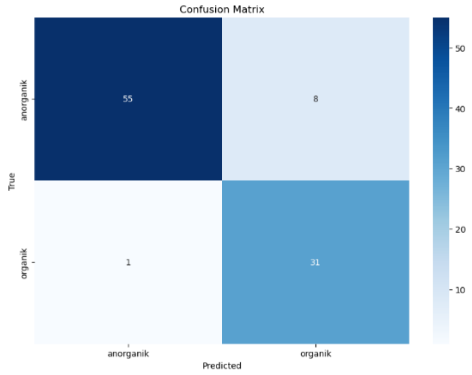
However, a closer analysis reveals that most prediction errors across the preprocessing scenarios involved waste that should have been classified as inorganic but was mistakenly predicted as organic. For instance, in S5-V1, there were 11 misclassifications where inorganic waste was predicted as organic waste, representing the highest error rate among all scenarios using MobileNetV1. Conversely, misclassifications of organic waste as inorganic waste were relatively rare, with error counts ranging from 1 to 3 across all scenarios.

On MobileNetV2, performance is generally lower compared to MobileNetV1, with a tendency for higher prediction errors. For instance, in the S3-V2 scenario, the highest number of errors was recorded, amounting to 21 errors, consisting of 19 misclassifications of inorganic waste as organic waste and 2 misclassifications of organic waste as inorganic waste. This indicates that preprocessing methods in certain scenarios can interfere with the model's ability to accurately distinguish between inorganic and organic waste.

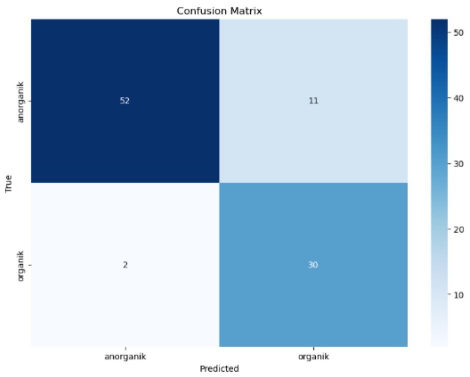


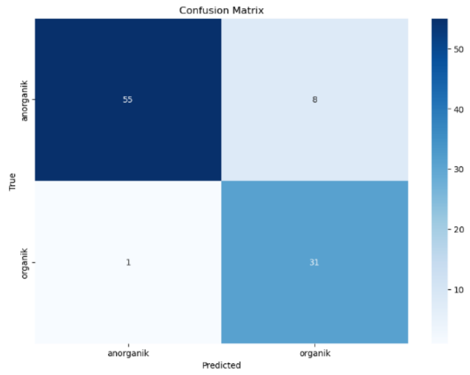
(a) (b)



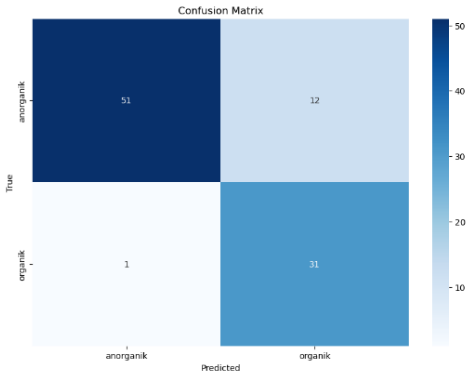


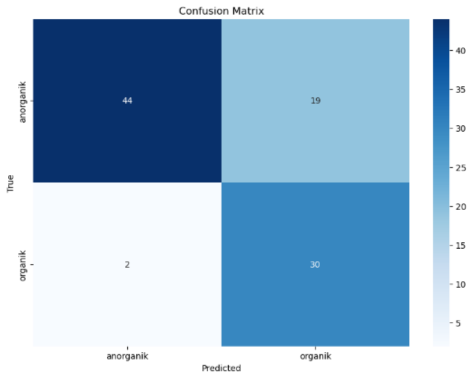
(c) (d)



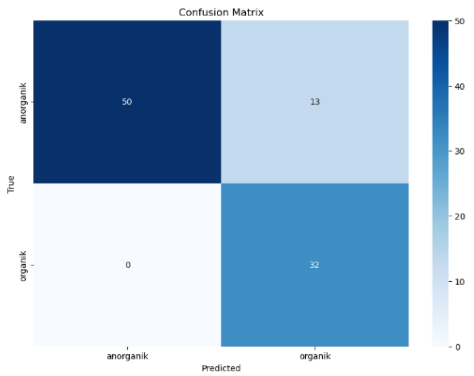


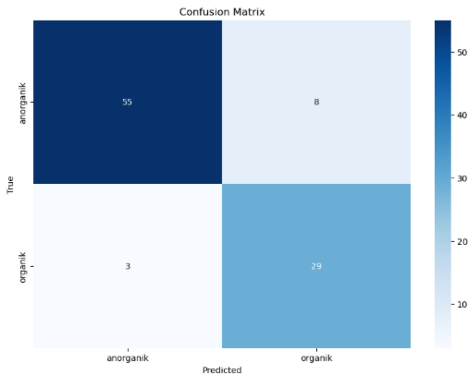
(e) (f)





(g) (h)





(i) (j)

Figure 9. Confusion Matrix (a) S1-V1, (b) S2-V1, (c) S3-V1, (d) S4-V1, (e) S5-V1, (f) S1-V2, (g) S2-V2, (h) S3-V2, (i) S4-V2, (j) S5-V2

4. Conclusions

The results of the study indicate that both models exhibit different responses to the preprocessing scenarios tested, with MobileNetV1 consistently outperforming MobileNetV2. Specifically, MobileNetV1 with the second preprocessing scenario which uses a combination of CLAHE and Bilateral Filtering, achieved the highest validation accuracy of 96%, with the lowest validation loss of 0.1630. this finding suggests that the combination of preprocessing methods can enhance model performance, as reflected in the accuracy and the prediction error rate observed from the confusion matrix. On the other hand, MobileNetV2 performed best in the first scenario (baseline), which did not involve any additional preprocessing. In the baseline scenario, MobileNetV2 exhibited better accuracy, and a lower prediction error rate compared to other scenarios that included additional preprocessing methods. Both additional preprocessing scenarios for MobileNetV1 and MobileNetV2, namely S2-V1 and S1-V2, required considerable processing times of 89.66 seconds and 99.87 seconds, respectively. Nonetheless, these times did not diminish the overall performance gains achieved. Evaluation results also showed that prediction errors were more likely to occur in the classification of inorganic waste being misidentified as organic waste. However, the error rate for MobileNetV1 was lower than that of MobileNetV2, indicating that MobileNetV1 was more effective at capturing distinguishing features even with additional preprocessing. The results of this study can be utilized to assist in the sorting of inorganic and organic waste through an artificial intelligence-based waste management application.

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